

RUNNING HEAD: BEHAVIORAL STAGES AND MINDSETS

Stages of Health Behavior Change and Mindsets: A Latent
Class Approach

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Abstract

Objective. Stage theories of health behavior are popular and of high practical relevance. Tests of the validity of these theories provide limited evidence because of validity and reliability problems. This study provides a bottom-up approach to identify behavioral stages from examining differences in underlying mindsets. We examine the concurrent validity of a latent-class based approach and a commonly used stage-algorithm based on self-reports about intentions and behavior in order to identify possible strengths and shortcomings of previously used approaches.

Methods. Social-cognitive variables and individuals' stages were assessed in a sample of 2219 internet users. Latent class analysis (LCA) was used to identify distinct groups with similar patterns of social-cognitive predictors. Convergent validity of the LCA solution and stage algorithms was tested by examining adjusted standardized residuals.

Results. The LCA identified four distinct profiles – not intending to change, intending to change (no action), intending to change with action, and maintaining. Convergent validity with a stage algorithm was low, in particular in the non-intending and maintaining stages.

Conclusion. Stages as assigned by the stage-algorithm did not correspond well with the extracted mindsets: This indicates that commonly used stage-algorithms might not be effective in assigning individuals to stages that represent mindsets, undermining the possibility for stage-matched interventions.

Keywords: Latent class analysis, Validity, Stage algorithm, Stage theories, Self report measure

Stages of Health Behavior Change and Mindsets: A Bottom-up Approach

In recent years, particularly in applied fields, stage theories of health behavior change have become increasingly popular. The idea that people pass through an ordered set of qualitatively different stages on their way to adopting new health behaviors is intuitively appealing and a *motif* for the description of many change processes (Brug et al., 2005). It also is highly attractive for practical applications, as it implies targeting specific intervention components for individuals in different stages, and suggests that such interventions are more effective than one-size-fits-all measures (Prochaska et al., 2004).

However, a crucial question beyond this attractiveness is the question about the construct validity of stages of health behavior change. In this article, we propose an alternative to current procedures examining the validity of stages, which heavily rely on the validity and reliability of the algorithms used for the measurement of stages as well as on the predefined ordering and boundaries of the stages. We argue that subgroups of individuals with a particular mindset towards health behaviors (as inherently assumed by the stage construct ; Weinstein, Rothman, & Sutton, 1998) can be more reliably inferred from the data using a latent class analysis approach. In a second step, we examine the convergent validity of a commonly used stage measure and these mindsets.

Discontinuity and Mindsets

Current tests of the construct validity of stage theories rely on the identification of discontinuity in the means or effects of relevant factors across the different stages that theories define (Weinstein, Rothman, & Sutton, 1998). The rationale underlying this quest for discontinuity is the assumption that during the process of change, individuals can have different mindsets towards behavior, and that these different mindsets manifest themselves in different cognitions. Mindset theory (Heckhausen, 1991; Heckhausen & Gollwitzer, 1987)

assumes that the mindset of an individual towards behavior changes as a result of cognitive and behavioral processes. One of the most basic differences between mindsets, which might serve as an example here, is the difference between a *deliberative* and an *implemental mindset*. Individuals in a deliberative mindset weigh the advantages and disadvantages of a specific behavior, finally resulting in a decision for or against the behavior. Individuals in an implemental mindset focus on executing this decision. Experimental studies support this assumption (Fujita, Gollwitzer, & Oettingen, 2007), (Taylor & Gollwitzer, 1995). This evidence accordingly suggests that deliberative and implemental mindsets are characterized by fundamentally different cognitions and cognitive processes.

The Stage Construct in Stage Theories of Health Behavior Change

Stage theories of health behavior adopt this idea of different mindsets by construing the process of health behavior change as progressing through different stages with differential mindsets. As the stages/ mindsets are defined by different cognitions and processes, they should be affected differentially by specific treatment content. Most stage theories however assume a more fine-graded stage distinction than just a deliberative and implemental mindset. For example, the Transtheoretical Model (TTM) (Prochaska, DiClemente, & Norcross, 1992) assumes that individuals pass through five distinct stages from precontemplation to maintenance. The Precaution Adoption Process Model (Weinstein, 1988) assumes no less than six stages from unaware of the issue to maintenance, and the Health Action Process Approach (Schwarzer, 1992) assumes two meta-stages and a number of finer-graded stages. All approaches, however, share transitions from non-intending to change behavior to intending to change behavior, the fundamental transition from intending to change behavior to actually changing behavior (Orbell & Sheeran, 1998), and from changing behavior to maintaining or habituation (Schüz, Sniehotta, Mallach, Wiedemann, & Schwarzer, 2009;

Schwarzer, 2008). This idea of qualitative differences between the stages is the logic underlying the tests for the validity of the stages.

Validity of Stage Theories – the Quest for Discontinuity

Most tests of the validity of stage theories rely on the idea that individuals in the same stage have mindsets that are more similar as compared to individuals' mindsets in another stage. As a consequence of this idea, various tests of the validity of stage theories can be formulated (Sutton, 2000; Weinstein, Rothman, & Sutton, 1998). These tests share the idea that the effects of a particular factor on the likelihood of subsequent stage transitions follow a discontinuous (non-linear) pattern across the stages (Balmford, Borland, & Burney, 2008a). For example, for cross-sectional data, Sutton (2000) requires that the means of stage-specific factors should follow a pattern that does not fit a linear trajectory across the stages but rather a quadratic, cubic or any other non-linear trend. A number of studies have examined such discontinuity patterns of means across stages and interpret these to support the validity of the underlying stage construct (Armitage, Povey, & Arden, 2003; Sniehotta, Luszczynska, Scholz, & Lippke, 2005) or as not supporting the stage assumptions (see e.g., Balmford, et al., 2008a; Balmford, Borland, & Burney, 2008b; Herzog & Blagg, 2007 for the TTM). As Weinstein and colleagues (1998) point out, such tests constitute the lowest level of evidence for a stage theory, since alternative explanations for the discontinuity patterns are possible, for example non-linear increases across the stages or reverse causality. Stronger evidence, according to Weinstein et al. (1998), is constituted by discontinuous predictors of stage transitions in longitudinal settings. Accordingly, a factor predicting transitions from an earlier stage to a later stage should only predict this transition if the underlying stage construct were true. This idea has been examined in a range of studies with moderate evidence strength for various predictors from risk perceptions over specific self-efficacy beliefs to social support in a range of health behaviors (Armitage, Sheeran, Conner, & Arden, 2004; Schüz, et al., 2009;

Wiedemann et al., 2009). The strongest evidence for the validity of stage theories comes from experimental matched-mismatched intervention studies, in which the idea of discontinuity is evident in the test for differential effects of the intervention according to the stage a person is in (Weinstein, Lyon, Sandman, & Cuite, 1998; Weinstein, Rothman, & Sutton, 1998).

Validity of the Validity Tests Revisited

A crucial issue in testing the construct validity of the stages concept is the way stages are operationalized. Most often, stage assessments are based on algorithms consisting of the answers to a number of questions with regard to the studied behavior (Godin, Lambert, Owen, Nolin, & Prud'homme, 2004), which can be more or less successful compared to other assessments of intentions or behavior (Lippke, Ziegelmann, Schwarzer, & Velicer, 2009). However, while such approaches are useful in examining whether individuals assigned to specific stages differ in the effects or means of variables deemed important, they rely on the limited reliability and sometimes limited validity of the underlying stage algorithm and stage theory (Balmford, et al., 2008b). There are both statistical and theoretical problems with such tests: Algorithms based on single items or combinations of single items can face a serious problem resulting from limited reliability as measurement errors cannot be corrected for in such assessment. In addition, ANOVA-based tests for discontinuity such as fitting linear or quadratic trends to mean differences or planned contrasts rely on the statistical assumption that there is equidistance or at least a monotonous increase or decrease between the stages. This statistical requirement however is not inherent in the stage definition of stage theories (see for example the arbitrary sequential order of the *decided to act* / *decided not to act* stages in the PPM (Weinstein, 1988)). Coming from a theoretical viewpoint, an examination of the idea that individuals differ in mindsets, i.e., differ in cognitions and cognitive processes, would require that differences in these cognitions are used to assign individuals to mindsets. This test is what this article aims at - providing a bottom-up assignment of individuals to

groups based on the similarity of their cognitions, and examine whether these groups match the predictions and allocations by stage algorithms. Furthermore, as stages of health behavior change are a social and scientific construct rather than an empirical entity (Schwarzer, 2008), a nomothetic approach prescribing a stage differentiation and sequence might be an oversimplification of the complex nature of human behavior change processes. Applying confirmatory approaches by examining discontinuity between arbitrary or at least a-priori-defined stages might therefore not be appropriate to examine mindset differences—an exploratory approach is better suited to examine the assumption of qualitative differences between stages or mindsets. In this article, we propose an alternative to such nomothetic top-down approaches by applying a bottom-up based approach, i.e., inferring differential mindsets from differences in cognitions and cognitive processes.

Inferring Mindsets from Social Cognitions: a Bottom-Up-Approach

As outlined above, the idea of qualitatively different stages of health behavior is based on the assumption of differential mindsets in stages (Heckhausen, 1991; Weinstein, Rothman, & Sutton, 1998). Our approach takes this idea of differential mindsets as starting point. Unfortunately, most stage theories are not very precise with regard to the factors that constitute a specific stage. The TTM (Prochaska, et al., 1992) proposes ten processes of change, but so far, tests have provided no evidence for the assumed stage-specific effects (Herzog, 2008). The PAPM makes differential assumptions for the effects of risk perception, which should be more important for stage transitions in early stages, and self-efficacy, which should be more important in later stages. The HAPA makes differential assumptions for the transitions from not intending to intending to change, and from intending to change to changing behavior: For transitions from the first stage, *risk perceptions*, *outcome expectations*, and *motivational self-efficacy* are assumed important, whereas for the transition from intending to acting, *coping self-efficacy*, *planning* and *cognitive action control* are

assumed important, while for the transition from acting to maintaining in particular *recovery self-efficacy* is deemed effective (Schwarzer & Luszczynska, 2008). These factors are also inherent in most theories delineating the determinants of intention formation (Schüz, et al., 2009), and the predictors of behavior change are similarly shared between various theories (Sniehotta, 2009). Assuming that these predictors comprise the most relevant factors for explaining behavior change, it should be possible to characterize individuals in different mindsets by a combination of levels of these factors—such as that individuals in an initial mindset before committing to a behavioral intention should have low perceptions of risk and low levels of proximal behavior predictors such as planning or action control, while individuals in a mindset aimed at pursuing a behavioral intention should score higher on such proximal factors and lower on factors such as negative outcome expectations. Our approach aims at identifying subgroups of individuals with similar patterns of the social cognitions inherent in most theories of behavior change. In order to test the convergent validity of our approach with a-priori defined stages, we compare the groups obtained by our approach to a generic stage algorithm based on self-reports of intentions and behavior (Lippke, et al., 2009; Richert, Lippke, & Schwarzer, 2010). This algorithm can serve as an example for other pre-defined staging approaches, for example those based on the TTM or the PAPM. If the approaches are not convergent valid, this would have strong implications for stage-based health behavior change interventions in that mismatches between intervention contents and intervention recipients become more likely, potentially resulting in ineffective interventions.

Research Questions

A valid and reliable stage measure (or algorithm) should assign individuals to stages that are an accurate reflection of individuals' mindsets (or in other words their patterns of social cognitions towards behavior). Subsequently, if a stage measure is valid, the classes that represent the social cognitive patterns should correspond well with the stages as assigned by a

stage algorithm. In this study, we aim at examining whether mindsets inferred from patterns of social cognitions in homogeneous subgroups match the predictions of stage allocation of a current stage algorithm based on intentions and behavior. These homogeneous subgroups of individuals will be identified using latent class analysis, a statistical technique assessing a categorical latent variable (e.g., the latent stage) in a data set constituting groups of individuals with maximally homogeneous patterns of predictors. Using this approach, it might be possible to overcome problems of limited reliability inherent in current stage algorithms, because it accounts for measurement error in its latent variable framework. It may also overcome problems of validity limitations as it goes beyond a nomothetic top-down approach by identifying differential mindsets from a bottom-up perspective.

Method

Procedure

The protocol for this study has received approval by the Internal Ethics Review Board of Freie Universität Berlin¹. Individuals were recruited for a web-based intervention study on fruit and vegetable consumption by press releases (radio, newspaper, TV) and advertisements posted on the university website. Participants visited a starting web page, and, after giving informed consent, were directed to a baseline questionnaire. As incentive, participants could take part in a raffle for online shop gift certificates. After the baseline questionnaire, which the current study is based on, participants were randomly allocated to one of four experimental groups for an intervention study (not reported here).

Participants

The dataset comprised $N=2220$ individuals. One participant was eliminated due to more than 50% missing values. Subsequently, the study sample consists of $N=2219$ individuals, who were on average $M=38.22$ years old (range=13-79, $SD=12.64$) and mostly

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women (80.8%). The majority of the sample was employed (63.5%) and in a steady relationship (59.3%). Almost half the sample was highly educated (43.6% College degree).

Measures

Unless otherwise noted, all items were rated on a 6-point Likert scale ranging from (1) not at all true to (6) exactly true. Scale means were computed, and scale values were dichotomized at the theoretical mean of 3.5 in order to facilitate interpretation of the latent classes.

Risk Perception was measured with three items adapted from Schüz et al. (2009): “If I continue to live this way, there is a high probability of me... (1) having a heart attack or stroke, (2) having diabetes, and (3) being obese.” Cronbach’s Alpha was .86.

Positive Outcome Expectancies were assessed with four items adapted from Schüz, et al. (2009): “If I eat sufficient amounts of fruits and vegetables every day, then... (1) I feel good and content, (2) I am doing something for my health, (3) I have good mental functioning, and (4) it has positive effects on my physical appearance.” Cronbach’s Alpha was .86.

Negative Outcome Expectancies were assessed using the same item stem followed by three statements: “(1) my food does not taste as good, (2) it will be a financial burden, and (3) then I will have to invest a lot of time and effort (e.g., grocery shopping, food preparation).” (Schüz et al., 2009). Cronbach’s Alpha was low with $\alpha = .54$, which indicates that the scale assesses diverse outcome expectancies.

Action Planning was assessed with three items based on (Sniehotta, Schwarzer, Scholz, & Schüz, 2005): “I have planned precisely... (1) which fruits and vegetables I will eat, (2) at which occasions (in which situations) I will eat fruits and vegetables, and (3) how I will eat my fruits and vegetables (e.g., cooked, cut up).” Cronbach’s Alpha was .88.

Coping Planning was assessed with two items: “I have planned precisely... (1) in which situations I need to be especially careful so as to succeed in eating sufficient amounts of fruit and vegetables and (2) what I can do in difficult situations so as to succeed in eating sufficient amounts of fruits and vegetables.” (Wiedemann et al., 2009). Items correlated significantly with $r=.68, p<.01$.²

Motivational Self-efficacy was measured with two items: “I am confident that I can/could eat sufficient amounts of fruits and vegetables...(1) even if it is difficult for me, and (2) even if there are few convenient shopping possibilities.” (Schüz et al., 2009). Items correlated significantly with $r = .55, p < .01$.

Coping Self-efficacy was measured with two items: “I am confident that I can keep eating sufficient amounts of fruits and vegetables...(1) even if I have to overcome obstacles (e.g., that there is no fruit or vegetable available at the grocery store I usually go to), and (2) even if I have problems or worries.” (Wiedemann et al., 2009). Items correlated significantly with $r = .62, p < .01$.

Recovery Self-efficacy was measured with two items: “I am confident that I can eat sufficient amounts of fruits and vegetables again...(1) even if I have failed to do so for a few days, and (2) even if I haven’t done so for quite some time.” (Wiedemann et al., 2009). Items correlated significantly with $r = .78, p < .01$.³

Action Control was assessed with three items based on (Sniehotta, Scholz, & Schwarzer, 2005): “I am aware of how many portions of fruits and vegetables I want to eat

² A confirmatory factor analysis (CFA) for the action /coping planning scales corroborated the assumed factorial structure: A two-factor model (action planning and coping planning) was contrasted with a one-factor model. The two-factor model fit the data better than the one-factor model: $\Delta\chi^2(1) = 38.85, p < .001$.

³ A second CFA corroborated the self-efficacy structure: A three-factor model (motivational self-efficacy, coping self-efficacy and recovery self-efficacy) was compared to a one-factor model. The three-factor model fit the data better than the one-factor model: $\Delta\chi^2(1) = 83.03, p < .001$.

daily.”, “I check whether or not I have eaten as many fruits and vegetables as I had intended.”, and “I am trying hard to eat as many fruits and vegetables as I had intended.” Cronbach’s Alpha was .87.

Stage assessment was based on previous studies (Lippke, et al., 2009; Richert, et al., 2010). Participants responded to the following two items: (1) “In the past week, have you eaten *enough* fruits and vegetables *per day*?” as well as (2) “In the near future, do you intend to eat more fruits and vegetables than you are eating now?”. Answers were given in a yes/ no format. Participants were classified as *Non-Intenders* on responding ‘no’ to both questions, as *Intenders* if they answered ‘no’ to the first and ‘yes’ to the second question, as *Maintaining Actors* if they responded ‘yes’ to the first and ‘no’ to the second question, and as *Changing Actors* if they answered ‘yes’ to both questions (stage labels from Richert, et al., 2010).

Insert Table 1 about here

Statistical Analyses

In order to identify mutually distinct subpopulations of individuals with similar profiles of social cognitive predictors of behavior (mindsets), we used latent class analysis (LCA). LCA aims at finding a parsimonious set of subgroups of individuals that are maximally similar with regard to the indicators (here: social cognitive predictors). Latent class indicators consist of distinct categories. The general idea behind LCA is similar to cluster analysis, but LCA carries the advantages of a latent (i.e., measurement-error free) variable approach, and the number of classes can be inferred using inferential statistics (Magidson & Vermunt, 2004). LCA assesses how likely it is for each individual to be a member of every extracted class. Individuals are then assigned to the latent class for which their assignment probability is highest. Class membership is mutually exclusive, so that each

individual is assigned to one class only. The model fit is evaluated by the Akaike information criterion (AIC) and Bayesian information criterion (BIC). Class solutions for different numbers of classes can be tested against each other based on the Lo-Mendell-adjusted bootstrapped likelihood ratio (LR) test, which compares an estimated model to a model of one less class than the estimated model (Lo, Mendell, & Rubin, 2001).

The research question of whether the LCA classes are convergent valid with the stages as obtained by the stage algorithm is tested by pitting the classes and the stages against each other. If correspondence were high, then individuals should be clustered around the diagonal of the stage by class matrix (i.e., the frequencies in corresponding cells, in which classes are matched against their stage counterpart, should be significantly higher than what is expected based on mere chance). Likewise, frequencies in non-correspondence cells (off-diagonal) should be lower than or equal to frequencies expected based on chance (Richert, et al., 2010). Statistically, this is tested by looking at adjusted standardized residuals, which are deviations of observed frequencies from frequencies that are expected based on chance. These deviation values are adjusted to the cell size and are approximately normally distributed. Thus, if values exceed the critical values ± 1.96 , 2.58, or 3.29 respectively, the number of cases found in that cell is significantly higher or lower than would be expected based on mere chance (Agresti, 2002).

Results

Results from Latent Class Analysis

As AIC values are relative, Burnham and Anderson (2004) suggest they be contrasted among competing models. Specifically, difference scores of ≤ 2 between the AIC value associated with the best approximating model and AIC scores of other models within the set are interpreted as similar competing models in terms of their approximating abilities. Values

within the range of 4 – 7 indicate models that have less support, and models with difference scores higher than 10 have no support relative to the best approximating model.

Insert Table 2 about here

The difference score of 1.163 indicates that the models supporting 4 and 5 classes are similar in terms of their approximating abilities. The BIC, however, is lowest for a 3 class solution. The LR test for the four-class model yielded a significant result (LR test value = -9162.58, $p < .001$), indicating that the four-class solution fits the data better than a three class model. For the five-class model, the LR test was non-significant (LR = -9142.234, $p = .37$), which indicated that the four-class model fits the data as good as the five-class model.

Although the models supporting 4 and 5 classes seem to fit the data equally well, the four-class solution is the most parsimonious model. We therefore decided to extract four latent classes, and figure 1 shows the profiles in terms of conditional solution probabilities. A solution probability close to 1 indicates a high likelihood of scoring high on the respective scale. Individuals were assigned to the class for which they had the highest probability scores. In this study, these probabilities were exceptionally high: class 1 = .91, class 2 = 1.0, class 3 = .97, class 4 = .93, indicating a high reliability of class assignment.

Insert Figure 1 about here

Members of class 1 (23.1% of all participants) had a moderate likelihood (.58) to score high on risk perception, the lowest likelihood to have high levels of motivational self-efficacy, and they were the least likely to perceive advantages of fruit and vegetable intake, while at the same time being the most likely to perceive disadvantages of the behavior

compared to all other classes. Furthermore, their likelihood to score high on volitional scales (i.e., Action Planning, Coping Planning, Coping- and Recovery Self-efficacy, and Action Control) was relatively low. This pattern resembles individuals in a deliberative mindset, i.e., *not intending to change*.

Individuals in class 2 (13.1%) were most likely to score high on risk perception (.68). Members of this class were also very likely to have high levels of motivational self-efficacy as well as to perceive advantages of fruit and vegetable intake. They had low likelihoods to perceive disadvantages of behavior. Their likelihood to score high on Action Planning, Coping Planning and Action Control was rather low, while their likelihood of scoring high on Coping- and Recovery Self-efficacy was high. This pattern resembles individuals who are not deliberating anymore, that is, individuals who are *inactive with an intention to change*.

Class 3 (27.9% of participants) had a zero likelihood of scoring high on risk perception. Individuals in this class were likely to have high levels of motivational self-efficacy as well as to perceive benefits of fruit and vegetable consumption. At the same time, they were very unlikely to perceive disadvantages of the behavior. Their likelihood of scoring high on Action Planning, Coping Planning and Action Control was low. Their likelihood to score high on Coping- and Recovery Self-efficacy was rather high. This pattern most resembles individuals *maintaining* behavior.

Members of class 4 (27.9%) had a moderate likelihood (.37) to score high on risk perception and to have high levels of motivational self-efficacy. They were very likely to perceive advantages of fruit and vegetable intake and very unlikely to perceive disadvantages of the behavior. Furthermore, their likelihood to score high on volitional scales (i.e., Action Planning, Coping Planning, Coping- and Recovery Self-efficacy, and Action Control) was high. This pattern resembles individuals with an *intention to change* something about *their current behavior*.

Test of LCA–Stage Correspondence

The stage algorithm appointed 43 individuals (1.9% of the total sample) to the Non-Intenders stage, the majority of participants ($n = 1591$, 71.7%) were categorized as Intenders, 235 individuals (10.6%) were labeled as Maintaining Actors and 350 people (15.8%) were classified as Changing Actors.

Insert Table 3 about here

Of the individuals placed in class 1, only 1.4% of individuals were classified as Non-Intenders based on the stage-algorithm (corresponding cell). This number was not higher than what would be expected based on mere chance (standardized adjusted residual = -1.1 , $p > .05$), indicating that there was no correspondence between class 1 and the Non-Intender stage. The majority of individuals assigned to class 2 (83.4%) were classified as Intenders based on the stage measure (corresponding cell). The frequency observed in this cell ($n = 242$) was significantly higher than the frequency expected based on chance ($n = 208$, standardized adjusted residual = 4.8 , $p < .001$). This indicates a high correspondence between class 2 and the Intender stage. Only 17.9% of the individuals, who were placed in class 3 were classified as Maintaining Actors (corresponding cell). The standardized adjusted residual of 7.0 ($p < .001$) shows that the observed frequency was significantly higher than what would have been expected based on chance. This indicates a good match. However, the frequency found in the cell pinning class 3 against the Changing Actor stage (non-corresponding cell) was also significantly higher than what would be expected based on chance (standardized adjusted residual = 6.7 , $p < .001$). Here, 24% of the individuals, who were placed in class 3 were classified as Changing Actors, indicating an equally good match between these categories. The majority of individuals assigned to Class 4 (83.7%) were classified as Intenders based on

the stage measure (non-corresponding cell). The frequency observed in this cell ($n = 667$) was significantly higher than the frequency expected based on chance ($n = 571$, standardized adjusted residual = 9.4, $p < .001$). This indicates a high correspondence between class 4 and the Intender stage. Only 10% of individuals assigned to class 4 were classified as Changing Actors (correspondence cell). The standardized adjusted residual of -5.5 ($p > .05$) revealed that the observed frequency was significantly lower than what would be expected based on chance, indicating that there was no correspondence between these categories.

As an overall measure of agreement, Cohen's Kappa was calculated. A κ of .02 indicates poor correspondence and thus corroborates the findings above.

Discussion

This study aimed at providing an alternative to current top-down tests of the validity of stages of behavior change. We examined the concurrent validity of a generic staging algorithm with mindsets based on patterns of social cognitions, which reflect qualitatively different mindsets of individuals in different stages of behavior change inherent in the stage construct (Weinstein, Rothman, & Sutton, 1998). Our results indicate poor correspondence between the allocations based upon a top-down staging algorithm and bottom-up latent classes of individuals with similar cognitions.

Mindsets and behavioral stages

Our study followed a bottom-up-approach, that is, we did not rely on somewhat arbitrary (Sutton, 2001) criteria such as the temporal references in the TTM to assign individuals to stages, but followed the idea of stage theories that individuals in qualitatively different stages of behavior change differ in their cognitions about specific behaviors (Weinstein, Rothman, & Sutton, 1998). This idea implies different mindsets of individuals in different stages. This should be evident in greater similarity of cognitions between

individuals *within* one stage than *between* different stages. Evidence from research on mindsets support this notion (Gollwitzer, Heckhausen, & Steller, 1990). Our analysis design accounts for this demand as latent class analysis infers latent classes and membership to these classes from similarities within and dissimilarities between classes (Magidson & Vermunt, 2004). In contrast to other group-identifying techniques such as cluster analysis, LCA, by way of the Chi²-difference-test, allows for statistically testing the number of latent classes.

This approach also allows for overcoming potential problems of confirmatory approaches that rely on limited reliability and validity of stage algorithms, as it is a latent variable procedure allowing for measurement-error-free assessment of latent classes. The bottom-up nature of our approach, that is, inferring latent classes representing different mindsets or stages from cognitions towards behavior, is close to the assumption of different mindsets inherent in stage theories. In contrast to tests for discontinuity of means or effects of specific variables between behavioral stages (Balmford, et al., 2008a; Herzog & Blagg, 2007; Sutton, 2000), our approach is not dependent on assumptions of equidistance or monotonous linear relations between stages. Although an ANOVA itself of course does not require equidistance or ordinal characteristics of the levels of the factor, the interpretation of statistical tests for trends between the levels of the independent factor does. A reordering of the levels of a factor might turn a linear trend into a quadratic one and vice versa. Our approach does not rely on such assumptions about sequence or equidistance between stages, but instead infers behavioral stages as qualitatively different mindsets from the data and as such might help future research on the validity of behavioral stages to overcome these limitations.

Additionally, as latent class analysis displays probabilities rather than certainties to score highly on a respective scale, it accounts for the possibility of individuals belonging in a particular class to score differently on that scale. This notion is important for the development

of stage-based interventions to promote health behavior change, because these are developed based on group means, i.e., they target variables that have been identified as predictors of behavior change in the majority of individuals in a particular class.

Behavioral Stages Identified by Latent Class Analysis

Our analysis identified four latent classes of social cognitions towards health behaviors that can be matched unto the stages defined in most stage theories (Schüz, et al., 2009): a stage *before* individuals have formed an intention, a stage *with* intentions but *without* behavior, a stage with maintained behavior and one with intended changes in current behavior (Lippke, et al., 2009).

Individuals classified into the first latent class match individuals in a stage *before* behavior change (a deliberative mindset). In this mindset individuals are more open to positive and negative information about behavior (Gollwitzer, et al., 1990), and the low levels of all post-intentional factors suggest that these individuals have engaged in little reasoning about behavior change.

Individuals classified in the second latent class match individuals in a stage *after* intention formation, but before actual behavior change. In contrast to individuals in the first latent class, they perceive high levels of positive outcome expectancies and low levels of negative outcome expectancies, which indicates an *implemental* mindset (Gollwitzer, et al., 1990), and could also serve the purpose to reduce discrepancy once a behavioral decision has been made. With regard to volitional factors, individuals in this latent class have low levels of action planning and coping planning, which may be explained by the fact that they have not initiated behavior change so far, but relatively high levels of coping and recovery self-efficacy. While especially this latter result might seem to contradict predictions made e.g., by the HAPA (Scholz, Sniehotta, & Schwarzer, 2005), tenets of self-efficacy theory can help in interpreting this result: An optimistic belief in one's abilities to overcome setbacks and to

recover from behavioral lapses can also be an important precondition of reasoning about behavior change, and only high levels of self-efficacy in these domains will help to commit to the goal of adapting a new behavior such as increased fruit and vegetable consumption.

Individuals classified in the third latent class show a profile of cognitions that matches individuals *maintaining* behavior. They score lowest on risk perception, reflecting the fact that their risk for diseases due to absence of nutritional health risk behavior is very low (Renner, Schüz, & Sniehotta, 2008; Weinstein, Rothman, & Nicolich, 1998). They also report low levels of cognitive action control, which might reflect the fact that fruit and vegetable consumption is habitual for them and requires little to no conscious effort (Wood, Quinn, & Kashy, 2002). In contrast to individuals assigned to class 4, individuals in this stage have a very low chance of scoring high on coping planning; possibly reflecting that due to habituation of behavior, no cognitive efforts for overcoming critical situations is needed.

Individuals allotted to latent class 4 match individuals in a stage with *some* behavior but *intended changes*. These individuals have especially high levels of action- and coping planning, and action control—cognitive indicators of ongoing behavior change processes and effective strategies to initiate and maintain behavior change (Sniehotta, Scholz, et al., 2005). This finding might be due to their increased efforts to change behavior and also because of better recall of such strategies due to the relative recency of their behavior change.

Correspondence Between Mindsets and Stages as Measured by a Stage Algorithm

As the LCA extracts social-cognitive profiles from the data (rather than confirming *a priori* set classes), it might be justified to infer that these profiles are an accurate reflection of qualitatively distinct mindsets. The reliability of the LCA solution (cf. probabilities in the results section) suggests that if stages and classes do not correspond well, the stage-algorithm might not be valid and reliable in assessing stages that are reflective of mindsets. Note that the algorithm used in this study reflects a generic approach to classify stages according to

intentions and behavior rather than relying e.g., on temporal criteria as in the TTM (Prochaska, DiClemente & Norcross, 1992). While this approach prevents us to evaluate the validity of specific stage theories and staging algorithms, the generic stages approach allows to illustrate the general usefulness of the mindset approach.

To understand the results, it is necessary to consider the frequencies that were observed and their relationship to the frequencies that were expected based on chance. For example, the observed frequencies alone suggest that the match between class 3 and the Intender stage is closer than the match between class 3 and any other stage (the majority of all individuals placed in class 3 were classified as Intenders). However, the frequency was significantly lower than what would have been expected based on chance, suggesting that the visible match is not tenable.

Although the profile of class 2 resembles individuals with a post-deliberative mindset (cf. Figure 1 as well as the results section), it corresponds equally well with the Non-intender Stage and the Intender Stage. This suggests that the algorithm is not successful in assigning individuals to stages that represent a definite mindset. The same holds true for class 3. The correspondence is equally high between this class and the Maintaining Actor and Changing Actor Stage. This ambiguity might result in incorrect classifications of individuals with the mindset of a maintaining actor as changing actors. Similar results were found for classes 1 and 4. Class 1 best corresponded with the Maintaining Actor stage and class 4 best matched the Intender Stage.

Our study suggests that a common generic stage-algorithm based on self-reports about intentions and behavior contains a high risk of misclassification. Although different stage algorithms might have produced different results, the generic algorithm represents the limitations inherent in all staging algorithms, namely limited reliability and unclear definitions of the factors that characterize behavioral stages. Our results can offer an

explanation for the sometimes found lack of supportive results in the field of stage-matched interventions (Adams & White, 2005; Bridle et al., 2005; Conn, Hafdahl, Brown & Brown, 2008; Noar, Benac & Harris, 2007). From a practical view our results suggest that health behavior change interventions based on stage theories might be limited in their effectiveness, if they are based on algorithms with limited validity and reliability. Ultimately, this could result in mismatches between intervention contents and recipients and ineffective interventions.

Limitations and Directions for Future Research

A limitation of our study relates to the fact that we have relied on self-reports of social cognitions. Research on mindsets has shown that differences between mindsets are also evident on the level of cognitive performance (Fujita, et al., 2007) and implicit cognitions (Custers & Aarts, 2007). Future research should consider this to distinguish mindsets. The latent classes we extracted are based on social cognitions, excluding intentions to change and behavior. Although future research may consider including both variables, we decided against it as we matched the social-cognitive profiles against stages as predicted by a measure relying on self-reports about intentions to change and behavior. We thereby avoided circular reasoning. While our cross-sectional data remains silent with regard to the validity of the mindsets for differential likelihoods and the predictors of behavior change, the internal and construct validity of the mindsets is supported both by the confirmatory approach used in latent class analysis and the divergent validity of the mindsets against the staging algorithm. Future studies might aim at examining the predictive validity of mindsets by e.g., examining whether behavior change is more likely for individuals in one specific mindset than in another and by using latent transition analysis. Our study employed only one generic staging algorithm to examine the concurrent validity of latent classes and stages. This clearly limits our results in terms of direct comparisons to other algorithms based on for example the TTM

or PAM. However, the generic algorithm used here shares the limitations of other algorithms in terms of reliability and underlying stage assumptions. Furthermore, it needs to be noted that the reliability of the scale assessing negative outcome expectancies as well as the correlation between the items assessing motivational self-efficacy were only moderate. More reliable measures may be considered in the future. In addition, the sample in this study was self-selected. Participants knew that the study targeted fruit and vegetable consumption, which might explain the low percentage of self-identified Non-Intenders. This limits the generalizability of our results.

Our study relied on the identification of latent classes from profiles of social-cognitive variables. These variables do not necessarily drive stage transitions. For example, both Non-Intenders and Maintaining actors have low risk perceptions. It does not follow however, that both groups need an intervention addressing risk perception as Maintaining Actors, e.g., have low levels of risk perception, because they take their preventive health behavior into account when estimating their risks. Future Research should further investigate if the process of change is different for different classes (characterized by different social-cognitive profiles). Only experimental research, where interventions that are tailored to classes are pitted against interventions that are mismatched, can really answer this question (Sutton, 2000).

Implications and Conclusion

The bottom-up approach used in this study has considerable advantages for the identification of distinct stages of health behavior change. Inferring stages from mindsets does not require equidistance or monotonous increase and still allows for statistical goodness-of-fit tests. Second, potential statistical problems of stage algorithms such as limited reliability are accounted for by the latent variable approach, and finally, a bottom-up approach might reveal more information about the actual mindsets of individuals in different

stages of health behavior change than a confirmatory top-down approach such as comparing means of variables in individuals across a-priori defined stages.

While it may not be feasible to assess a wide range of variables before allocating individuals to stages and administering interventions, our results underline the importance of assessing stages in a reliable and valid way. If stage-based interventions were to work, it is crucial to target the factors most important within one stage. Our approach suggests an alternative to current staging algorithms by extracting groups of individuals based on their mindsets towards behavior, which could ultimately result in more reliable and valid assessments of stages and consequently more effective stage-based interventions.

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TABLE 1. Means (*M*), Standard Deviations (*SD*), and Intercorrelations for all social-cognitive variables in *N* = 2119 participants

	Risk Perception	Motivational Self-efficacy	Positive Outcome Expectancies	Negative Outcome Expectancies	Action Planning	Coping Planning	Coping Self- efficacy	Recovery Self- efficacy	Action Control
<i>M</i>	3.35	4.61	4.85	2.7	3.32	2.81	4.15	4.86	2.79
<i>SD</i>	1.33	0.95	0.70	0.98	1.20	1.20	1.04	0.84	1.16
Risk Perception	1.00								
Motivational Self-efficacy	-.002	1.00							
Positive Outcome Expectancies	-.08*	.22*	1.00						
Negative Outcome Expectancies	.24*	-.23*	-.10*	1.00					
Action Planning	-.14*	.14*	.23*	-.15*	1.00				
Coping Planning	-.10*	.13*	.23*	-.11*	.61*	1.00			
Coping Self-efficacy	-.12*	.38*	.22*	-.29*	.15*	.19*	1.00		
Recovery Self-efficacy	-.20*	.31*	.25*	-.28*	.17*	.14*	.45*	1.00	
Action Control	-.12*	.11*	.25*	.10*	.47*	.54*	.21*	.15*	1.00

Note. * $p < .01$

TABLE 2. AIC and BIC Values for Different Latent Class Analysis Models

Models	AIC	BIC
1 class	19644.978	19696.321
2 classes	18649.156	18757.547
3 classes	18383.153	18548.593
4 classes	18362.468	18584.956
5 classes	18361.305	18640.841
6 classes	22331.134	22975.829

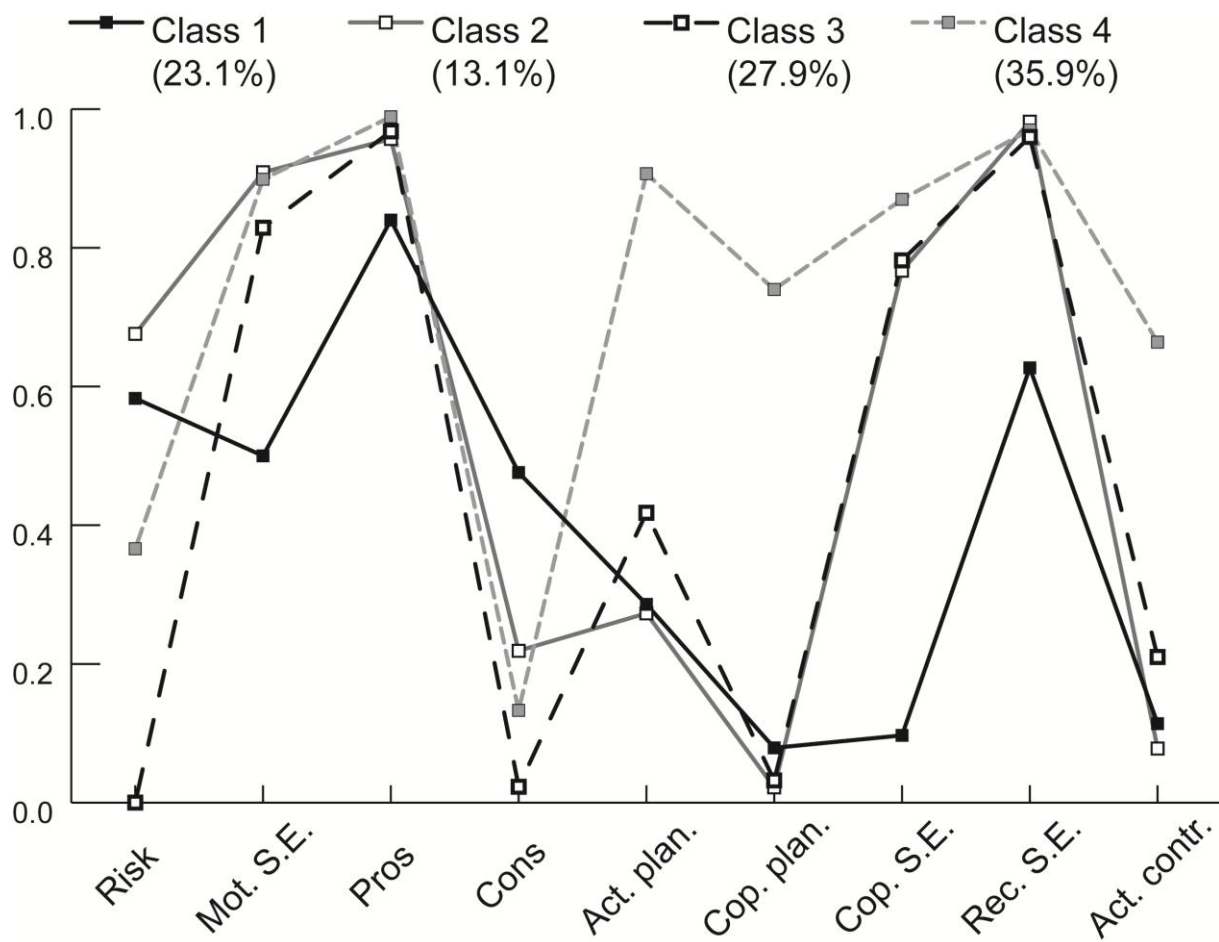
TABLE 3. Frequencies for LCA classes and for stages as obtained by a stage measure.

		Latent Classes extracted by the LCA					
		Class 1	Class 2	Class 3	Class 4	total	
Stages assigned by the stage measure	NI	observed <i>N</i>	7	15	6	15	43
		expected <i>N</i>	10	6	12	15	
		stand. adj. residuals	-1.1	4.3***	-2.1*	-0.1	
		% within LCA classes	1.4%	5.2%	1.0%	1.9%	
		% within stages	16.3%	34.9%	14.0%	34.9%	
		% of total <i>N</i>	0.3%	16.9%	0.3%	0.7%	1.9%
	I	observed <i>N</i>	329	242	353	667	1591
		expected <i>N</i>	368	208	444	571	
		stand. adj. residuals	-4.3***	4.8***	-9.5***	9.4***	
		% within LCA classes	64.1%	83.4%	57.0%	83.7%	
		% within stages	20.7%	15.2%	22.2%	41.9%	
		% of total <i>N</i>	14.8%	10.9%	15.9%	30.1%	71.7%
	MA	observed <i>N</i>	79	10	111	35	235
		expected <i>N</i>	54	31	66	84	
		stand. adj. residuals	4.0***	-4.2***	7.0***	-7.1***	
		% within LCA classes	15.4%	3.4%	17.9%	4.4%	
		% within stages	33.6%	4.3%	47.2%	14.9%	
		% of total <i>N</i>	3.6%	0.5%	5.0%	1.6%	10.6%
	CA	observed <i>N</i>	98	23	149	80	350
		expected <i>N</i>	81	46	98	125.7	
		stand. adj. residuals	2.4*	-3.9***	6.7***	-5.5***	
		% within LCA classes	19.1%	7.9%	24.1%	10.0%	
		% within stages	28.0%	6.6%	42.6%	22.9%	
		% of total <i>N</i>	4.4%	1.0%	6.7%	3.6%	15.8%
total	observed <i>N</i>	513	290	619	797	2219	
	% of total <i>N</i>	23.1%	13.1%	27.9%	35.9%		
	% of female participants	85.2%	74.1%	86.9%	75.8%		
	Mean age	34.82	37.82	39.07	39.91		

Note. NI, Non-Intender; I, Intender; MA, Maintaining Actor; CA, Changing Actor; stand. adj.

residuals, standardized adjusted residuals; expected *N*s are rounded; * $p < .05$, *** $p < .001$

FIGURE 1 Latent class profiles for the four-class model.



Note. Risk = risk perception, Mot. S.E. = motivational self-efficacy, Pros = positive outcome expectancies, Cons = negative outcome expectancies, Act. Plan. = Action Planning, Cop. plan. = Coping Planning, Cop. S.E. = Coping Self-efficacy, Rec. S.E. = Recovery self-efficacy, Act. contr. = Action Control.